# Dynamic Analysis of the Sustainable Performance of Electric Mobility in European Countries

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**Abstract.** As part of the ongoing climate and energy framework, the European Commission raised recently the 2030 greenhouse gas emission reduction target, moving towards a climate-neutral economy. Transportation represents almost a quarter of Europe's greenhouse gas emissions, and it is the remaining sector with increasing emissions, above 1990 levels. Considering also the evolving necessity for the reduction of fossil fuels dependency, Europe's strategy has been designed to support an irreversible shift toward low-emission electric mobility. In this context, the present work assesses the performance of electric mobility in European countries, by using a dynamic analysis in the period 2015-2019, framed in four sustainable dimensions, economy, technology, environment and society. The methodology aggregates several sub-indicators in a composite indicator by using the Data Envelopment Analysis, and evaluates the dynamic change in the sustainable performance through the biennial Malmquist index. Main results indicate that the total productivity change has been improved mainly due to the progression of the frontier that has been observed for all countries from 2018. However, an increasing number of countries have had more difficulties to adopt the best sustainable electric mobility practices, being necessary to design strategies to promote them, mainly in underperforming countries.

**Keywords:** Electric mobility · Composite Indicator · Malmquist index.

## 1 Introduction

Under the European strategy for low-emission mobility framework, Member States have been under guiding principles to increase the efficiency and the sustainability of the transport system, through the deployment of low emission alternative energies and by accelerating the transition towards low and zero emission vehicles [11].

This strategy grips the targeted greenhouse gas (GHG) emissions reduction on the 2030 climate and energy policy framework, as stated in the Regulation (EU) 2018/842 [13]. The transport sector represents almost a quarter of the Union's GHG emissions and it remains as the only sector that has increased steadily the emissions until 2019, when compared with 1990 levels, diverging from the other sectors [17]. Estimates for

2020 indicate a substantial reduction due to decreased activity during COVID-19 pandemic, but European Environmental Agency (EEA) anticipates that transport emissions will deteriorate with the economic recovery and it is projected that domestic transport emissions will stay above 1990 levels till 2029 [12].

Besides, the need for dependency reduction on imported fossil fuels has become crucial due to instability in many fossil fuel-producing countries, which increases the price of energy and reinforces the need to find alternatives.

Under this scenario, the sustainable performance of the electric mobility in European Union is able to drive innovation while enhancing risk management and cost reduction and provides engagement at all levels. By monitoring and analysing the trends towards low-emission mobility, it is possible to exploit deviations and set up guidelines, to provide policy makers with decision tools to design their strategies.

The sustainable model for a given programme, agenda, development or sector, usually requires its evaluation by several perspectives, termed pillars. Early sustainable concepts were evaluated through the Economy growth, Social inclusion and balance of the Environment [22]. Several authors suggested the use of a fourth pillar, the cultural sustainability, which, in a broader scope, can be incorporated in the Social sustainability, focusing on human issues [18]. The economic sustainability is typically described at a country or region level and aims at translating the ability to support a specified level of economic production. With regard to the environmental pillar, it aims to enhance the natural capital and/or the welfare of the population [18].

In the particular sector of the electric mobility, the sustainable framework should also include the dimension of the technological development and innovation. For instance, long-term energy storage is crucial in the penetration of battery electric vehicles (BEV).

This paper aims to evaluate the sustainable performance of the electric mobility in European countries in a dynamic timeline framework, from 2015 until 2019. As stated before, due to reduced activity during COVID-19 pandemic, the time series does not include data from 2020. The methodological approach aggregates sub-indicators in the four sustainable dimensions introduced above: economic, social, environmental and technological into a composite indicator (*CI*) by using the Data Envelopment Analysis (DEA) technique. Thus, the sustainable performance, *CI*, is determined through the Benefit of Doubt (BoD) model [4] and to track the change of the sustainable performance of electric mobility, it is used the biennial Malmquist index [20], considering it was originally developed to assess the Malmquist productivity change index [1]. In this context, the proposed approach is innovative because the biennial Malmquist index allows the dynamic analysis of the sustainable performance of electric mobility in European Countries as it can be decomposed into the technical change (frontier shift effect) and efficiency change (catching-up effect) [20]. The frontier shift effect allows to identify the deterioration or progression on the European best practices of sustainable electric mobility while catching-up effect gathers the evolution of each country against the best practices observed in each period.

A previous review performed by the authors [17] identified the main relevant indicators and analysed the methodologies most employed in literature for assessing the deployment of electric mobility. This survey establishes the basis for the selection of the indicators, aiming to convey the affordability, the infrastructure availability, GHG reduction levels and educational level, the latter as a predictor of environmental protection support willingness.

With regard to the electric mobility, in opposition to conventional vehicles using exclusively fossil fuels (diesel and petrol) and/or natural gas (compressed or liquefied) to power an internal combustion engine (ICE), the alternatives can be categorised as electric vehicles (EV) or hybrid electric vehicles (HEV), with different requirements in terms of the support infrastructure.

Electric vehicles can be further subdivided in plug-in electric vehicle (PEV), *i.e.*, electrically-chargeable vehicles, and fuel cell electric vehicles (FCEV).

PEV include full battery electric vehicles (BEV) and plug-in hybrids (PHEV), both requiring a recharging infrastructure to connect them to the electricity grid. BEV are fully powered by one or more electric motors, using electricity stored in an on-board battery and the PHEV have an ICE and a battery-powered electric motor. The battery is recharged by connecting to the grid as well as by the on-board engine. The traction is provided by the electric motor and/or by the ICE, depending on the battery level.

Fuel cell electric vehicles (FCEV) also run on electric motors, but the electricity is generated within the vehicle by a fuel cell, using compressed hydrogen, from dedicated filling stations, and oxygen from the air. The state of art of the production, transport and distribution of hydrogen and the lack of filling stations does explain the negligible share of FCEV in the European passenger car fleet.

Finally, hybrid electric vehicles (HEV) have an internal combustion engine and a battery-powered electric motor. Electricity stored in the on-board battery is generated internally from regenerative braking, cruising and the combustion engine, so they do not need recharging infrastructure. The hybridisation level can range from mild to full, depending on the type of propulsion combination (powered by the combustion engine with the electric motor supporting it, or propulsion shared by both electric motor and combustion engine, respectively).

Cumulative to the different requirements in terms of the infrastructure mentioned above, these technologies have also different impacts on the GHG emissions reduction levels. BEV and FCEV have a tail-pipe $CO_2$ emissions reduction of 100%, while HEV have a reduction potential ranging from 10% to 40%, depending on the hybridisation level. Finally, PHEV have, on average, 50% to 75% potential for emissions reduction [9]. Regarding the later, it should be mentioned that the emissions reduction potential strongly depends on usage and charging behaviour. Recent studies from the International Council on Clean Transportation indicate that actual PHEV fuel consumption and emissions are higher than the levels in which they are approved, biasing the governmental support at the vehicle purchase and the accounting in the GHG emissions targets [21]. From this point of view, existing EU policies may shift in a near future for the PHEV market. Considering the time span of the data used in this study, the sustainability analysis of the passenger electric mobility is performed considering the electrically-chargeable cars, *i.e.*, BEV and PHEV.

This paper unfolds as follows: the methodology regarding the BoD model, the biennial Malmquist index, and the data are introduced in Sect. 2. Sect. 3 presents the results and discussion, including the performance assessment and the dynamic analysis, and Sect. 4 concludes this paper.

## 2 Methodology

DEA is a linear and non-parametric technique to evaluate the relative efficiency of an homogeneous set of Decision Making Units (DMUs) in using multiple inputs to achieve multiple outputs, introduced by Charnes et al. [2]. This enables to identify the "best practices DMUs" in which their linear combination defines the frontier technology. A single summary measure of efficiency is calculated for each DMU by using the frontier technology as a reference. The DMUs which belong to the frontier have an efficiency score equals to 1 while the remaining ones have an efficiency score lower than 1.

### 2.1 BoD Model

In the case of pure models, in which only use outputs, denominated by sub-indicators, Cherchye et al. [4] introduced the BoD model to compute the composite indicator for each DMU. The BoD model is equivalent to the DEA input oriented model [3], as all sub-indicators are considered as outputs and a single dummy input equal to one is used for all units. The BoD model enables to aggregate several sub-indicators to derive the composite indicator for each DMU, by determining endogenously the weights to aggregate them. Since BoD model does not refer the inputs, it enables to assess its performance rather than its efficiency [5].

Considering a cross-section of $m$ sub-indicators $i$ for each country $j$ $(j = 1, \ldots, s)$, being $y^t_{ij}$ the score of that sub-indicator observed for each country $j$ on the period $t$, and $w_i$ the weight assigned to it. The BoD model (1) assesses the performance for each country under assessment, $j_0$, to determine its composite indicator, $CI^t_{jo}$ through the weighted average of the $m$ sub-indicators.

$$
\begin{aligned}
&\mathrm{CI}^t_{j_0} = max \sum_{i=1}^{m} w_i y^t_{ij_0} \\
&s.t. \qquad \sum_{i=1}^{m} w_i y^t_{ij} \leq 1 \qquad \forall j = 1, \ldots, s \\
&\qquad\qquad w_i \geq 0 \qquad \forall i = 1, \ldots, m
\end{aligned}
\tag{1}
$$

For each country under evaluation $j_0$ in the period $t$, the model (1) determines endogenously the optimum weight $w_i$ for each sub-indicator $y^t_{ij_0}$ to maximize its $CI^t_{jo}$ by comparison with the frontier technology. Thus, the optimum weighting scheme varies with the country under evaluation to maximize its performance.

The model (1) does not avoid to assign zero weights to some sub-indicators, if the unit has a relative poor performance, implying no influence on its evaluation. In the opposite case, if a country has an high relative performance in a given sub-indicator, the model can assign a high weight to this dimension. To avoid these situations, proportional virtual weight restrictions (2) are imposed to the unit under evaluation [24]. Thus, each sub-indicator is required to have a minimum and maximum percentages of contribution on the calculation of the $CI^t_{jo}$ for the country under evaluation. Since no expert information is available, and setting $M$ the number of sub-indicators, constraint (2) should guarantee that the proportional virtual weight for each sub-indicator should vary between $\frac{1}{M}(1-k)$ and $\frac{1}{M}(1+k)$, with $k \in ]0,1[$ for the unit under evaluation. Decision maker should select the $k$ by balancing some flexibility, in which unrestricted model is the most flexible alternative, and consistency which allows that all dimensions are taking into account on the unit under evaluation.

$$\frac{1}{M}(1-k) \leq \frac{w_i y^t_{ij_0}}{\sum_{i=1}^{M} w_i y^t_{ij_0}} \leq \frac{1}{M}(1+k) \qquad \forall i = 1, ...M, k \in ]0,1[ \tag{2}$$

## 2.2 Biennal Malmquist Index

Malmquist productivity change indexes have been the most commonly used approach to estimate total factor productivity change between two data points, corresponding to a DMU in two time periods [20]. The Malmquist productivity index was introduced by Caves et al. [1] and developed further in the context of performance assessments by Färe et al. [15] to accomplish performance comparisons of DMUs over time, by taking the geometric mean of the Malmquist productivity index achieved in the periods $t$ and $t+1$.

The biennal Malmquist index is introduced by Pastor and Lovell [20] by considering a frontier technology $B$ defined by the convex hull of the frontier technologies concerning the periods $t$ and $t+1$ , given by $B = t,\ t+1$.

The Malmquist productivity index is based on radial measures which are defined by Shepard distance functions [23]. The score of $CI^t_{j0}$ in the model (1) is equal to the DEA radial efficiency score given by the Shephard output distance function [16], being equal to $D^t(1, y^t_o)$. Set $y^t_o$ the sub-indicators vector observed for the DMU$_o$ in period $t$, the distance function to the period $t$ frontier is given by $D^t(1, y^t_o)$.

Thus, the superscript inside brackets represents the period in each DMU$_o$ is assessed while the superscript outside of brackets denotes the frontier technology used as reference.

The biennial Malmquist index [20] derived for each DMU$_o$ is given by (3).

$$M^B_o = M^B_o(1, y^t_o, y^{t+1}_o) = \frac{D^B(1, y^{t+1}_o)}{D^B(1, y^t_o)} = EC_o.TC_o \tag{3}$$

In terms of interpretation, a score of $M^B_o(1, y^t_o, y^{t+1}_o) > 1$ indicates better productivity (global performance) in period $t+1$ than in period $t$ for the DMU$_o$.

The biennial Malmquist index $M^B_o$ enables to measure the total productivity change over time, and can be decomposed into the efficiency change index ($EC_o$) and the technical change ($TC_o$) index [20]. The catching-up effect is given by the efficiency change index for each DMU$_o$ according to (4).

$$EC_o = \frac{D^{t+1}(1, y^{t+1}_o)}{D^t(1, y^t_o)} \tag{4}$$

The score $EC_o$ compares the efficiency spread between the periods observed for each DMU$_o$. A value of $EC_o > 1$ ($EC_o < 1$) means that the efficiency spread is smaller in DMU$_o$ observed in period $t+1$ than the one observed in period $t$, measuring how much the DMU$_o$ is getting closer from the frontier, *i.e.* catching up effect (farther from the frontier).

The frontier shift is captured by the technical change index for each DMU$_o$, calculated by (5).

$$TC_o = \frac{D^B(1, y_o^{t+1})/D^{t+1}(1, y_o^{t+1})}{D^B(1, y_o^t)/D^t(1, y_o^t)} = \frac{BPG^{B,t+1}(1, y_o^{t+1})}{BPG^{B,t}(1, y_o^t)} \tag{5}$$

The ratio $TC_o$ compares the best practice gap ($BPG^{B,t+1}(1, y_o^{t+1})$) between the biennial frontier $B$ and the $t+1$ frontier along the ray defined by $(1, y_o^{t+1})$ with the best practice gap ($BPG^{B,t}(1, y_o^t)$) between the biennial frontier $B$ and the $t$ frontier along the ray defined by $(1, y_o^t)$.

When $TC_o$ is higher (lower) than 1, it indicates that the $t+1$ frontier is closer to (farther away from) the biennial frontier $B$ along the ray defined by $(1, y_o^{t+1})$ than is the $t$ frontier along the ray defined by $(1, y_o^t)$, *i.e.*, it measures the technological progress (regress) of the frontier, revelling better (worse) productivity.

Globally, the decomposition of $M_o^B$ implies that the sources of better performance can be associated with two factors: less dispersion in the efficiency score of DMU$_o$ between the two periods and/or better productivity associated to the period frontier. The calculation of the biennial Malmquist index and its components is explored in the next section by using a small example.

### 2.3 Illustrative Example

Suppose that two sub-indicators $y_1$ and $y_2$ are achieved for two periods $t$ and $t+1$ concerning four DMUs (A, E, C and D) as shown in the Fig. 1. This example is used to illustrate the calculation of $M_o^B$, its components $EC_o$ and $TC_o$, given in Table 1, and their interpretation. The frontier in the period $t$ $(t+1)$ is defined by the DMUs A and C observed in the period $t$ $(t+1)$ while the biennial frontier $B$ is defined by the DMUs $A^{t+1}$ and $C^t$. Between the two periods, the frontier only has a progression for the DMU A ($A^{t+1}$), and a regression on the frontier is observed on the other remaining DMUs, which is captured by the technical change index ($TC_o$).

As shown in the Fig. 1, DMUs A and C are efficient in both periods, so the $EC_o = 1$. The DMU E improves its efficiency between the two periods, as it is getting closer (*i.e.* catching up) from the frontier since the $EC_E > 1$. The opposite occurs for the DMU D as $EC_D < 1$, as it is getting farther from the frontier. For the DMU A in $t$ period, the frontier $t$ has a lower productivity than the frontier $B$, implying $BPG^{B,t} < 1$. For the DMU A in $t+1$ period, the frontier $t+1$ has the same productivity than the frontier $B$, implying $BPG^{B,t+1} = 1$. Thus, $TC_A > 1$ implies a progression in the frontier for the DMU A. The DMU A improves the total productivity ($M_A^B > 1$) due to the increase of the technical change, keeping the efficiency status between the two periods.

For the DMU E in $t$ period, the frontier $t$ has a lower productivity than the frontier $B$, implying $BPG^{B,t} < 1$. For the DMU E in $t+1$ period, the frontier $t+1$ has a lower

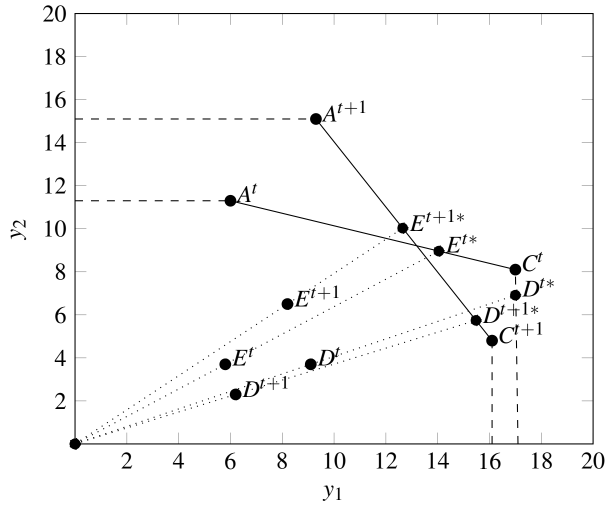


**Fig. 1.** Illustrative example.

**Table 1.** Results of $M_o^B$, $EC_o$ and $TC_o$ for DMUs A, E, C and D.

| DMU | $D^t(1,y_o^t)$ | $D^{t+1}(1,y_o^{t+1})$ | $D^B(1,y_o^t)$ | $D^B(1,y_o^{t+1})$ | $EC_o$ | $BPG_o^{B,t}$ | $BPG_o^{B,t+1}$ | $TC_o$ | $M_o^B$ |
|---|---|---|---|---|---|---|---|---|---|
| A | 1.000 | 1.000 | 0.748 | 1.000 | 1.000 | 0.748 | 1.000 | 1.336 | 1.336 |
| E | 0.413 | 0.648 | 0.381 | 0.592 | 1.570 | 0.922 | 0.914 | 0.991 | 1.555 |
| C | 1.000 | 1.000 | 1.000 | 0.947 | 1.000 | 1.000 | 0.947 | 0.947 | 0.947 |
| D | 0.535 | 0.401 | 0.535 | 0.365 | 0.748 | 1.000 | 0.910 | 0.910 | 0.681 |

productivity than the frontier $B$, implying $BPG^{B,t+1} < 1$. Thus, $TC_E < 1$ implies a deterioration on the productivity of frontier for the DMU E. The DMU E improves the total productivity ($M_E^B > 1$) due to the increase of efficiency change.

For the DMUs C and D in $t$ period, the frontier $t$ coincides with the frontier $B$, implying $BPG^{B,t} = 1$. For these DMUs in $t+1$ period, the frontier $t+1$ has a lower productivity than the frontier $B$, implying $BPG^{B,t+1} < 1$. Thus, $TC_o < 1$ implies a deterioration on the productivity of frontier for the DMU C and D. The DMU C decreases the total productivity ($M_C^B < 1$) due to the decrease of technical change, keeping the efficiency status in both periods. The DMU D decreases the total productivity ($M_D^B < 1$) due to the decrease of the technical change and efficiency change.

### 2.4 Data

To perform the sustainable performance analysis of the electric mobility in EU-28, several indicators were selected and aggregated in four sustainable dimensions, in accordance with a previous literature survey [17]. Data was collected from literature and online databases, and processed on a yearly basis, for the time period 2015 till 2019. Table 2 presents an overview of the selected indicators organized by the dimensions to sustainable development, the units, and identifies the data sources (Eurostat [14], European Commission (EC) [10] and European Alternative Fuels Observatory (EAFO) [8]). The contextualization and a brief description of the indicators are presented below.

The deployment of the electric mobility is largely correlated with the affordability and the infrastructure availability, under the economic and technological pillars, respectively.

The economic sustainability is supported by two indicators: the energy intensity of the Gross Domestic Product (GDP), given by the ratio between the gross inland energy consumption and the GDP, and the annual average fuel price for petroleum products (euro-super 95 and automotive gas oil). The first one is an anti-isotonic indicator [6], because higher values reflect inefficiencies in the economy and the second one, with regard to the sustainability of the electric mobility, push consumers to invest in solutions that are more economical.

Technological sustainability relates with cheap energy storage systems and long-lasting batteries, able to increase the driving range of BEV, which cannot be translated in a simple indicator. Measurable technological sustainability is given by the number of recharging points normalized by the number of inhabitants and also the market share of electrically-chargeable vehicles, evaluated by the ratio between the newly registered BEV and PHEV and the total newly registered passenger vehicles, per year.

To capture the environmental sustainability, the analysis includes the contribution of GHG emissions from fuel combustion in road transport to the total GHG emissions inventory, consisting in an anti-isotonic attribute. To prevent penalizations of countries with high industrial activity and, consequently, higher GHG emissions, this pillar also includes the industrial production index (IPI), measuring the industry productivity in a given year relative to the base year of 2015. Also, the share of renewable energy in transport with regard to gross final energy consumption is included as renewables impact largely in the environmental sustainability of the sector.

Finally, under the social sustainability dimension, the tertiary education attainment is inserted in the analysis, as a predictor of the willingness of the population to support environmental protection measures. This assumption takes into consideration that people are prone to reduce emissions if they understand the risks from climate change [19].

**Table 2.** Overview of the selected indicators.

| Variable | Description (source) | Source | Units |
|---|---|---|---|
| **Economy** | | | |
| *Energy intensity* | Energy intensity of GDP in chain linked values (2010) | Eurostat | (koe/$10^3$ €) |
| *Fuel price* | Fuel price for petroleum products with taxes | EC | (€/L) |
| **Technology** | | | |
| *Recharging points* | Number of recharging points per 100 hundred inhabitants | EAFO/Eurostat | n.a. |
| *Market share* | Market share of electrically-chargeable vehicles (BEV & PHEV) | EAFO | % |
| **Environment** | | | |
| *GHG emissions* | GHG emissions from fuel combustion in road transport | Eurostat | $\frac{\text{tonnes of CO}_2\text{-eq}}{\text{inhabitant}}$ |
| *IPI* | Industrial production index (base year 2015) | Eurostat | % |
| *Renewable* | Share of renewable energy in transport | Eurostat | % |
| **Society** | | | |
| *Education* | Tertiary education attainment in the 15-64 age group | Eurostat | % |

The descriptive statistics of the data on a yearly basis is presented in Table 3. The overall mean variation between 2015 and 2019 is also included.

**Table 3.** Descriptive statistics of the variables on a yearly basis.

| | 2015 | | 2016 | | 2017 | | 2018 | | 2019 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sub-indicator | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Variation |
| **Economy** | | | | | | | | | | | |
| *Energy intensity* | 173.611 | 83.817 | 172.695 | 82.492 | 172.025 | 82.353 | 167.414 | 81.090 | 159.350 | 73.459 | -8% |
| *Fuel price* | 1.252 | 0.124 | 1.154 | 0.121 | 1.234 | 0.127 | 1.332 | 0.125 | 1.325 | 0.130 | 6% |
| **Technology** | | | | | | | | | | | |
| *Recharging points* | 12.853 | 20.677 | 17.455 | 28.538 | 23.271 | 37.080 | 28.807 | 45.175 | 36.601 | 58.235 | 185% |
| *Market share* | 0.009 | 0.019 | 0.009 | 0.013 | 0.011 | 0.012 | 0.018 | 0.019 | 0.029 | 0.034 | 224% |
| **Environment** | | | | | | | | | | | |
| *GHG emissions* | 1.946 | 1.692 | 1.975 | 1.596 | 1.999 | 1.581 | 2.026 | 1.658 | 2.042 | 1.653 | 5% |
| *IPI* | 1.000 | 0.003 | 1.026 | 0.028 | 1.072 | 0.042 | 1.096 | 0.066 | 1.105 | 0.079 | 11% |
| *Renewable* | 0.065 | 0.053 | 0.062 | 0.047 | 0.069 | 0.051 | 0.078 | 0.052 | 0.088 | 0.053 | 35% |
| **Society** | | | | | | | | | | | |
| *Education* | 0.275 | 0.069 | 0.282 | 0.071 | 0.289 | 0.071 | 0.298 | 0.072 | 0.306 | 0.074 | 11% |

The overall behaviour of the sub-indicators favours the sustainable performance of electric mobility in the EU, except for GHG emissions, still increasing beyond 1990 levels. A substantial increase in the technological sub-indicators, market share of electrically-chargeable vehicles and number of recharging points, represent a solid shift towards low-emission mobility. It is also of relevance the increase of renewable energy in the transport sector, favouring the sustainability of the electric mobility. The decrease in the energy intensity of GDP acts also as a positive trend in pursuing the EU energy targets, through the efficiency increase of the processes.

## 3 Results and Discussion

This section analyses the sustainable performance of the electric mobility in European countries observed in each year and explores its change over time.

Thus, the sustainable performance of the electric mobility is calculated by the $CI^t$ for each year $t$ abbreviated by $t = 15, 16, 17, 18$ and 19. Further, its dynamic analysis is investigated, by calculating the biennial Malmquist indexes and their components, as described in the methodology.

The $CI^t$ for each year $t$ is calculated from the $M = 8$ sub-indicators listed in Table 3 by using the BoD model (1) and including the constraints given by (2), in which the $k = 0.9$ is adopted to assure the suitable flexibility and consistency. This $k$ score assures that each sub-indicator has a minimum contribution of $\frac{1}{8}(1-0.9) = 1.25\%$ and a maximum contribution of $\frac{1}{8}(1+0.9) = 23.75\%$ to the $CI^t$ score calculated for each country under evaluation in each period $t$.

Additionally, all selected sub-indicators must be isotonic, satisfying the assumption of the BoD model that higher sub-indicator scores correspond to better performance. This requires the transformation of GHG emissions and Energy intensity sub-indicators by subtracting the original values from a larger constant number [7] (*i.e.*, a constant equal to 10% higher than the maximum value observed in the sample for all countries and years).

### 3.1 Performance Analysis

The results concerning the $CI^t$ for each year $t,\ t = 15, 16, 17, 18$ and 19 and country[4] are presented in Table 4. The best practices frontier in the year $t$ is defined by the best practices countries observed on that year.

It is observed that there are only two benchmarks on sustainable electric mobility which are NET and SWE which keep the efficiency status in all years. Note, that there is no optimum solution for CYP in 2015 with the weighting scheme in use, denoting that it has some low levels of sub-indicators compared to the benchmarks. The direct comparison of $CI^t$ scores for each country enables to understand if the country has came closer (*i.e.* catching up) or further to the frontier. This effect is captured by the efficiency change index given by $EC_o$ that is calculated for each successive years according to (4), which scores are presented in Table 4. We can conclude that, on average, the European countries are getting closer to the frontier of the best practices on sustainable electric mobility until 2018, although they are getting farther from the frontier in 2019. These results do not indicate if the frontier has moved upward or downward which is explored in the dynamic analysis.

### 3.2 Dynamic Analysis

The biennial Malmquist $M_o^B$ index and its components, the efficiency change, $EC_o$, and the technical change, $TC_o$, are determined by using the panel data concerning the selected sub-indicators of 28 European Countries in each pair of successive years (2015/16, 2016/17, 2017/18, 2018/19), as presented in Table 4. Thus, the biennial frontier is defined by the best practices countries in terms of sustainable electric mobility observed on each pair of successive years.

In 2015/16, there are 21 countries that improve the total productivity ($M_o^B > 1$) mainly due to increase of efficiency change ($EC_o > 1$ is observed in 16 countries), and the progression of the frontier ($TC_o > 1$) that is observed in only 11 countries.

In 2016/17, all countries improve their total productivity ($M_o^B > 1$) except CRO. This is mainly due to increase of efficiency change ($EC_o > 1$ is observed on 21 countries), and the progression of the frontier that is observed for 25 countries ($TC_o > 1$). It is observed that the frontier deteriorates ($TC_o < 1$) for CZE, CRO and ITA. Additionaly, DEN, EST, GRE, CRO and UK increase their efficiency spread ($EC_o < 1$).

In 2017/18, all countries improve their total productivity ($M_o^B > 1$) mainly due to increase of technical change ($TC_o > 1$) since the progression of the frontier is observed in all countries. Although, 13 countries decrease their efficiency spread ($EC_o > 1$).

[4]The country notation of Eurostat [14] is adopted.

**Table 4.** Results of $CI^t$, $EC_o$, $TC_o$ and $M_o^B$

| | $CI^t$ | | | | | 2015/16 | | | 2016/17 | | | 2017/18 | | | 2018/19 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | $CI^{15}$ | $CI^{16}$ | $CI^{17}$ | $CI^{18}$ | $CI^{19}$ | $EC_o$ | $TC_o$ | $M_o^B$ | $EC_o$ | $TC_o$ | $M_o^B$ | $EC_o$ | $TC_o$ | $M_o^B$ | $EC_o$ | $TC_o$ | $M_o^B$ |
| BEL | 0.80 | 0.86 | 0.88 | 0.89 | 0.90 | 1.08 | 1.00 | 1.08 | 1.02 | 1.04 | 1.06 | 1.01 | 1.03 | 1.04 | 1.01 | 1.03 | 1.04 |
| BUL | 0.13 | 0.13 | 0.32 | 0.31 | 0.28 | 0.97 | 1.22 | 1.18 | 2.54 | 1.14 | 2.90 | 0.98 | 1.15 | 1.12 | 0.91 | 1.26 | 1.14 |
| CZE | 0.46 | 0.51 | 0.58 | 0.58 | 0.51 | 1.13 | 0.95 | 1.07 | 1.14 | 0.95 | 1.08 | 1.00 | 1.24 | 1.23 | 0.87 | 1.24 | 1.08 |
| DEN | 0.95 | 0.91 | 0.89 | 0.94 | 0.94 | 0.95 | 0.95 | 0.90 | 0.98 | 1.04 | 1.02 | 1.05 | 1.10 | 1.16 | 1.00 | 1.03 | 1.03 |
| GER | 0.74 | 0.84 | 0.90 | 0.89 | 0.86 | 1.13 | 0.97 | 1.09 | 1.07 | 1.05 | 1.12 | 0.99 | 1.05 | 1.04 | 0.97 | 1.04 | 1.00 |
| EST | 0.55 | 0.50 | 0.46 | 0.76 | 0.63 | 0.91 | 1.10 | 1.00 | 0.92 | 1.10 | 1.01 | 1.66 | 1.00 | 1.67 | 0.83 | 1.13 | 0.94 |
| IRE | 0.82 | 0.87 | 0.91 | 0.90 | 0.87 | 1.06 | 0.94 | 1.00 | 1.04 | 1.04 | 1.08 | 1.00 | 1.10 | 1.09 | 0.96 | 1.09 | 1.05 |
| GRE | 0.15 | 0.13 | 0.12 | 0.14 | 0.12 | 0.84 | 1.19 | 1.01 | 0.98 | 1.21 | 1.19 | 1.10 | 1.10 | 1.21 | 0.90 | 1.34 | 1.21 |
| ESP | 0.49 | 0.69 | 0.81 | 0.77 | 0.71 | 1.40 | 0.94 | 1.32 | 1.17 | 1.03 | 1.21 | 0.95 | 1.13 | 1.07 | 0.92 | 1.15 | 1.05 |
| FRA | 0.87 | 0.90 | 0.91 | 0.91 | 0.88 | 1.03 | 1.00 | 1.04 | 1.01 | 1.02 | 1.03 | 1.00 | 1.05 | 1.05 | 0.97 | 1.06 | 1.02 |
| CRO | 0.43 | 0.55 | 0.49 | 0.57 | 0.62 | 1.28 | 0.98 | 1.25 | 0.88 | 0.91 | 0.81 | 1.18 | 1.19 | 1.41 | 1.08 | 1.24 | 1.35 |
| ITA | 0.50 | 0.55 | 0.62 | 0.64 | 0.71 | 1.10 | 0.95 | 1.05 | 1.13 | 0.93 | 1.05 | 1.04 | 1.32 | 1.36 | 1.10 | 1.08 | 1.18 |
| CYP | - | 0.63 | 0.63 | 0.59 | 0.51 | - | - | - | 1.01 | 1.06 | 1.07 | 0.92 | 1.11 | 1.02 | 0.88 | 1.20 | 1.05 |
| LAT | 0.48 | 0.55 | 0.57 | 0.75 | 0.62 | 1.14 | 0.99 | 1.13 | 1.04 | 1.07 | 1.11 | 1.31 | 1.03 | 1.35 | 0.83 | 1.17 | 0.97 |
| LIT | 0.26 | 0.30 | 0.51 | 0.57 | 0.49 | 1.15 | 1.16 | 1.33 | 1.70 | 1.04 | 1.76 | 1.11 | 1.12 | 1.24 | 0.87 | 1.22 | 1.06 |
| LUX | 0.72 | 0.82 | 0.85 | 0.86 | 0.84 | 1.14 | 0.96 | 1.08 | 1.04 | 1.09 | 1.13 | 1.02 | 1.07 | 1.09 | 0.97 | 1.07 | 1.04 |
| HUN | 0.47 | 0.47 | 0.52 | 0.63 | 0.59 | 1.00 | 1.05 | 1.05 | 1.11 | 1.12 | 1.24 | 1.21 | 1.05 | 1.27 | 0.94 | 1.13 | 1.06 |
| MAL | 0.61 | 0.49 | 0.71 | 0.78 | 0.75 | 0.80 | 0.85 | 0.68 | 1.47 | 1.16 | 1.71 | 1.08 | 1.11 | 1.20 | 0.97 | 1.08 | 1.05 |
| NET | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.07 | 1.07 | 1.00 | 1.09 | 1.09 | 1.00 | 1.26 | 1.26 |
| AUS | 0.86 | 0.88 | 0.90 | 0.90 | 0.88 | 1.03 | 1.02 | 1.05 | 1.02 | 1.02 | 1.04 | 1.00 | 1.04 | 1.04 | 0.98 | 1.03 | 1.01 |
| POL | 0.25 | 0.25 | 0.33 | 0.36 | 0.32 | 0.98 | 1.04 | 1.02 | 1.35 | 1.08 | 1.46 | 1.08 | 1.14 | 1.24 | 0.89 | 1.31 | 1.17 |
| POR | 0.80 | 0.83 | 0.87 | 0.84 | 0.80 | 1.04 | 0.99 | 1.03 | 1.04 | 1.05 | 1.09 | 0.98 | 1.07 | 1.04 | 0.95 | 1.07 | 1.01 |
| ROM | 0.15 | 0.14 | 0.18 | 0.18 | 0.29 | 0.93 | 1.19 | 1.11 | 1.34 | 1.20 | 1.60 | 0.98 | 1.13 | 1.11 | 1.59 | 1.22 | 1.94 |
| SLN | 0.64 | 0.71 | 0.77 | 0.80 | 0.73 | 1.11 | 0.97 | 1.08 | 1.08 | 1.07 | 1.16 | 1.04 | 1.02 | 1.06 | 0.91 | 1.13 | 1.02 |
| SLK | 0.48 | 0.49 | 0.70 | 0.67 | 0.54 | 1.03 | 0.88 | 0.90 | 1.41 | 1.15 | 1.63 | 0.96 | 1.15 | 1.11 | 0.80 | 1.21 | 0.97 |
| FIN | 0.95 | 0.89 | 0.94 | 0.92 | 0.96 | 0.94 | 1.01 | 0.96 | 1.05 | 1.06 | 1.11 | 0.98 | 1.05 | 1.03 | 1.04 | 1.07 | 1.11 |
| SWE | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.02 | 1.02 | 1.00 | 1.09 | 1.09 | 1.00 | 1.13 | 1.13 | 1.00 | 1.08 | 1.08 |
| UK | 0.95 | 0.98 | 0.98 | 0.97 | 0.97 | 1.03 | 1.00 | 1.03 | 1.00 | 1.04 | 1.04 | 1.00 | 1.03 | 1.02 | 0.99 | 1.03 | 1.03 |
| Average | 0.61 | 0.64 | 0.69 | 0.72 | 0.69 | 1.04 | 1.01 | 1.05 | 1.16 | 1.07 | 1.25 | 1.06 | 1.10 | 1.16 | 0.97 | 1.14 | 1.10 |
| $No. > 1$ | - | - | - | - | - | 16 | 11 | 21 | 21 | 25 | 27 | 13 | 28 | 28 | 6 | 28 | 25 |
| $No. < 1$ | - | - | - | - | - | 9 | 15 | 5 | 5 | 3 | 1 | 13 | 0 | 0 | 20 | 0 | 3 |
| $No. = 1$ | 2 | 2 | 2 | 2 | 2 | 2 | 1 | 1 | 2 | 0 | 0 | 2 | 0 | 0 | 2 | 0 | 0 |

In 2018/19, almost all countries improve their total productivity ($M_o^B > 1$) except EST, LAT and SLK. This is mainly due to increase of technical change ($TC_o > 1$) since the progression of the frontier is observed in all countries. Nevertheless, only 6 countries decrease their efficiency spread ($EC_o > 1$) which are BEL, DEN, CRO, ITA, ROM and FIN.

## 4 Conclusions

This paper presents an innovative approach to assess the dynamics of the sustainable performance of electric mobility in European Countries, from 2015 until 2019.

The sustainable performance is determined through the Benefit of Doubt (BoD) model [4] and it is used the biennial Malmquist index [20] to track the change of the total sustainable performance of electric mobility which can be decomposed into the efficiency change (catching-up effect) and technical change (frontier shift effect).

The catching-up effect gathers the evolution of each country against the best practices observed in each period by comparing the efficiency spread between the periods observed for each country. The frontier shift effect allows to identify the deterioration or progression on the European best practices of sustainable electric mobility by computing the technical change. Thus, it compares the best practice gap between the biennial frontier $B$ and the $t+1$ frontier along the ray defined by the observed country in $t+1$ with the best practice gap between the biennial frontier $B$ and the $t$ frontier along the ray defined by the observed country in $t$. The biennial frontier is defined by the best practices countries in terms of sustainable electric mobility observed on each pair of successive years.

Effectively, the total productivity change has been improved through time mainly due to the progression of the frontier since the best practices of sustainable electric mobility have been improved over time, as progression of the frontier was observed for all countries from 2018. Although the majory of the countries were getting closer to the frontier during 2016 and 2017, the opposite effect occurred in 2018 and 2019. From these results, it is observed that despite an upward of the frontier in the last two years of the analysis, the countries are getting farther from the frontier. This implies that an increasing number of countries have had more difficulties to adopt the best practices of the benchmarks. Our study indicates that is necessary to reinforce the actual policies to promote the electric mobility penetration, mainly in underperforming countries.

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